A Triangle Division Based Point Matching for Image Registration

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Abstract. One basic requirement of image registration is the high precision of point matching. In this paper, we present a simple and robust method to get more accurate matching points by using the structural information of divided triangles. The method initially construct triangles using Delaunay Triangulation which considering rough matched points as vertices, and then iteratively removes outliers until obtain the consensus topology structure. An algorithm called K-Nearest Neighbor Dis-ratio is also presented to avoiding mismatches. Compared with RANSAC and GTM, Our proposed method acquires more inliers and demonstrates higher matching accuracy.

Introduction

Image registration has been widely applied in remote sensing, medical image analysis, pattern recognition and many other computer vision applications.There are two main matching methods in image registration field: area-based matching and featured-based matching.It is unreliable and also time consuming when getting start from area based matching, so feature based matching has been widely used in image registration job.

S. Umeyama[1] discussed an approximate solution to the Weighted Graph Matching Problem (WGMP) for both undirected and directed graphs. W. Aguilar[2] proposed their point matching method named Graph Transformation Matching (GTM), Their method relies on finding a consensus nearest neighbor graph emerging from candidate matches, and eliminates dubious matches until obtain the final consensus graph. Inspired by GTM, Z. Liu[3] calculated the similarity of two points by comparing local neighbor spatial order using cyclic string matching method.

In this paper, we present a triangle division based point matching method which combining existing feature descriptors with global spatial constraints to remove mismatches and confirm ambiguities. The method firstly constructs triangles using Delaunay triangulation which considering rough matched points as vertices, and then iteratively removes outliers until obtain the consensus topology structure, it can also confirms the ambiguous matches from uncertain matching candidates by comparing their positions with divided triangles relatively.

The Triangle Division Based Matching

Crude Matching. By improving the NNDR[4] algorithm, we introduce a new method called K-Nearest Neighbor Dis-ratio. It firstly find more than one matching points for every significant point. Suppose P_i is a key point in image 1, Q_j $(j=1,2,\ldots,K$) is the *jth* nearest points to P_i in image 2, d_k is the Euclidean distance for SIFT[5] descriptor between P_i and its *kth* nearest neighbor Q_k. If $d_1/d_2 > R, d_1/d_3 > R,\ldots,\ d_1/d_k > R$ and $d_1/d(k+1) < R$, we consider $d_1,d_2,\ldots,d_k$ as the matching candidates of P_i ($k<K$, R is a set threshold which determined by processed images), but if d_1/d_k is still greater than R, we give up all these matching candidates and ignore this current point P_i.

Delaunay Based Triangle Division Matching. Assuming that candidate points in two images have been extracted and their crude mapping couples have been established: $P_{1:1}$ (one to matching) and $P_{m:n}$ (m to n matching), next step is to find the correct one to one correspondences. Most of our

images are based on perspective projection model, according camera model, we know that perspective projection of the same plane possess stable structure invariance property. Based on this precondition, our method is mainly to find the matching Delaunay Triangulation geometric topology relationship.

We first remove the false positive and reserve the true positives from the crude one to one matching sets. The theory of judging the true positive or false positive is checking whether the set of matching points is geometrically consistent. The main workflow of removing false positive and reserve true positives can be described with pseudo code as follows:

```
while ( sizeof(P1:1) != sizeof(Vr) )
{
  Delaunay P1:1 , get triangles' edges E;
  select a triangle Tr randomly,
  reserve its edges Er and vertexs Vr and there correspondence E'r , V'r;
  for (i =1;i<sizeof(E);i++)
  {
      if (Ei ∩ Er ⊂ Vr )
        for (j=1;j<sizeof(E'r );j++)
        {
          if ( E'i ∩ E'r,j ⊄ V'r )
            {remove VEi from P1:1;  break;}
        }
      if (j==sizeof(E'r ))
        {Er =Er +Ei ; Vr =Vr +VEi ;}
      else  break;
  }
```


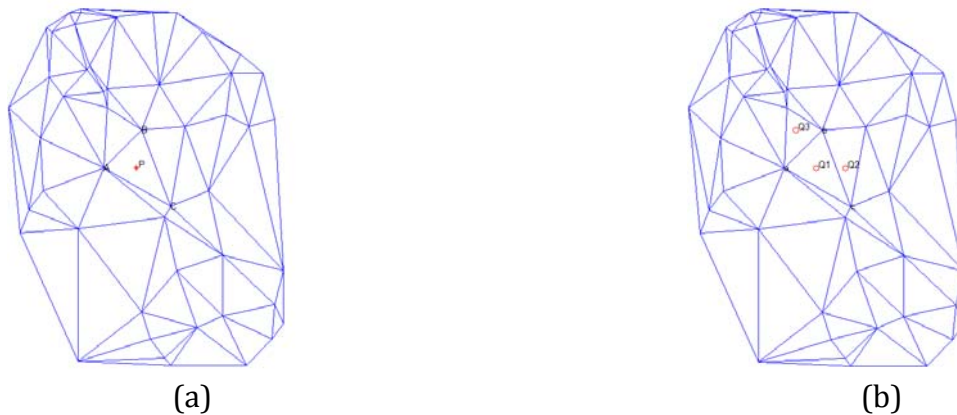(a)   (b)

Fig. 1 Delaunay based triangle division matching

Since the right *1:1* matches have been established, we refine m:n matches by checking the relationship between points and patterns. Suggest the blue triangles in Fig.1(a) and Fig.1(b) are consistent triangulation, and the vertices of these triangles are correct matched key features(e.g. points A,B,C in Fig.1(a) to points a,b,c in Fig.1(b) respectively). Key feature point P in Fig.1(a) matches key feature points Q_1, Q_2 , Q_3 in Fig.1(b). We find that point *P* is inside of $\triangle ABC$ in Fig.1 (a), the correspondence of *P* in Fig.1(b) should obey a same geometric topology relationship. Apparently, point Q_1 is inside $\triangle abc$ just like *P* while both of Q_2 and Q_3 are outside of $\triangle abc$, so keep the correct matches Q_1,and remove the other two incorrect matches Q_2 and Q_3. After one iteration finished, we update the correct one to one matches and confirm more matches during the next iteration. We get the last matching result after iteration stops for no more correct matches found.

Experiment and Analysis

In this section, we compare our method against RANSAC and GTM. In RANSAC case, the distance threshold is set to be 5 pixels, the desired probability *p* of choosing at least one sample free from outliers is set to be 0.99. In the case of GTM, a K-NN graph is created with the value of K=3.

Planar Matching with Ambiguities. Our first example is to process images with many analogous contents. We selected many image couples contain similar regions. Representatively, teaching buildings matching is a good choice for their windows are very alike mutually.

Fig.2(a) and Fig.2(b) are the GTM figure, we can see that although points in the marked blue circles have same number of adjacent points, they actually are not matched points. Fig.3(a) and Fig.3(b) present the global triangle mapping derived from our method which show a consistent topology distribution.
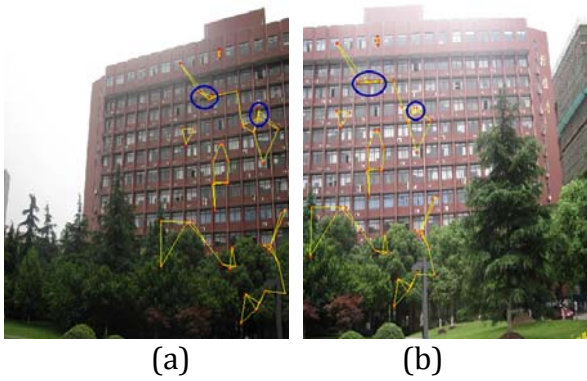
(a)	(b)

Fig. 2 GTM matching
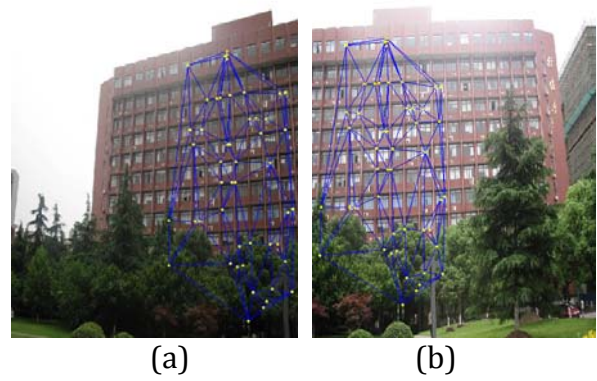
(a)	(b)

Fig. 3 Our Triangulation result

Fig.4 expresses the recall of these three methods in which X axis shows the outlier percentage increased from 0% to 50%. From this graph, we can see that Delauany overwhelms the other two methods obviously. Even the outliers rise to 45%, Delauany can still obtain more than 80% inliers. As to GTM algorithm, when the outliers is less than 20%, it can detect about 70% or more correct matches, but as the outliers grows, its recall value reduces quickly which means it can only obtain less and less useful points. RANSAC performs worst for it can just get less than 50% correct matching couples.

We also count their precision graph in Fig.5. It can be seen that both Delaunay and RANSAC give high precision value, and it is clear that Delaunay and RANSAC get nearly no mismatches even the under the situation of 50% outliers. GTM provides a slightly lower precision rate than RANSAC and Delaunay when the outliers are less than 20%, but it can't keep a good performance while the outliers increasing.
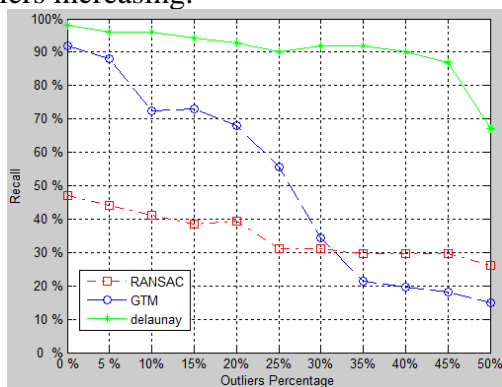

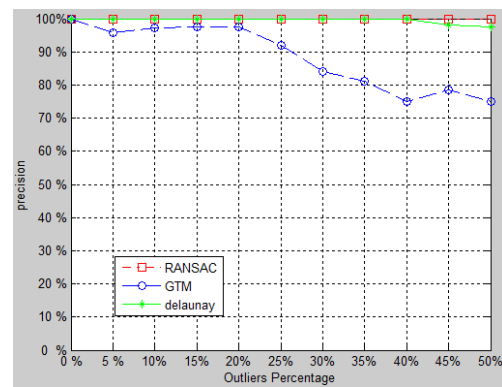Fig. 4 Recall for planar matching with ambiguities

Fig. 5 Precision for planar matching with ambiguities

Multi-planar Matching. When encounter images including multi planes which can't assumed as one plane approximately, RANSAC exposes its shortcoming inevitably for it is base on two-dimensional coordinate transformation rule. In Fig.6(a) and Fig.6(b), the final points obtained by RANSAC gather in the left plane and no points in the right plane are extracted, it means RANSAC can just get seldom points when abundant planes in the scene. Our method can avoid this restriction which can be proved in Fig.7(a) and Fig.7(b), we could see that our method extracts points from both the left and right planes successfully.
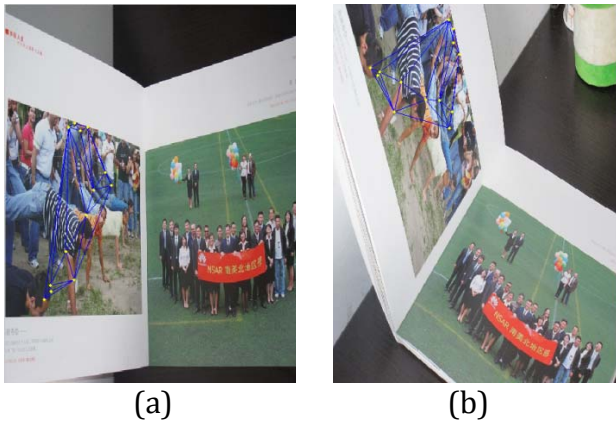
(a)   (b)

Fig. 6 RANSAC result of multi-planar matching

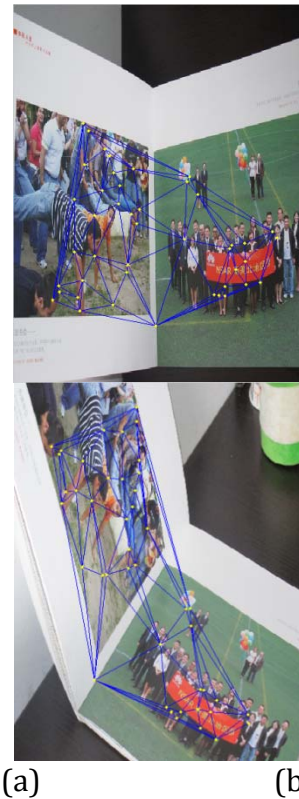(a)   (b)
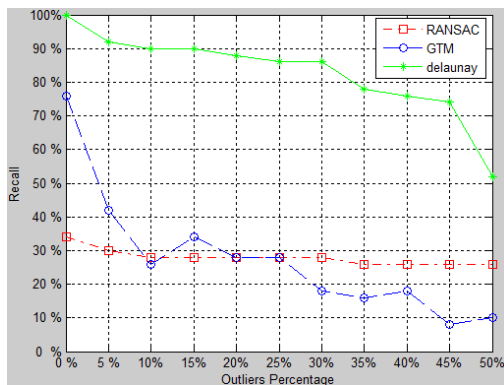
Fig. 7 Our result of multi-planar matching

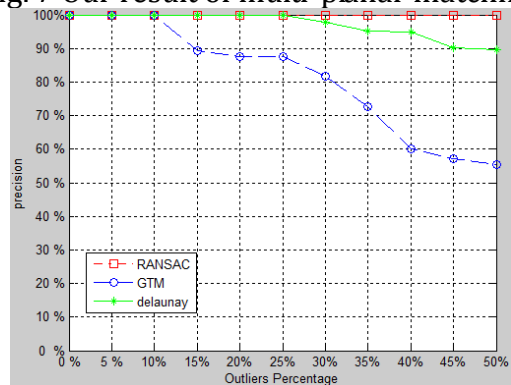Fig. 8 Recall for multi-planar matching

Fig. 9 Precision for multi-planar matching

Fig.8 and Fig.9 show the recall and precision like previous section. It can be seen that our method provides much higher recall value than RANSAC and GTM, which means our method can get more correct points in multi-planar matching situation. What inspires us is that our method always got a high precision value when the outlier percentage increased from 0% to 50%.

Conclusion

In this paper, we have introduced a new method to increase the point matching precision in image registration application. This method is accomplished mainly combine the local features and global graphic distribution relationships. In the experiments, our method exhibited outstanding performance both in the amount of matching points and the accuracy of matching result.

References

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